GROUND-TRACKING FOR ON AND OFF-ROAD DETECTION OF LANDMINES WITH GROUND PENETRATING RADAR

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ABSTRACT

Ground penetrating radar is a high-resolution electromagnetic technology that has demonstrated excellent potential for high probability of detection while keeping false alarm rate low for landmine detection in on-road tests. Off-road situations require more advanced methods for dealing with the most significant reflection in GPR data, the ground bounce. Performance enhancements achieved via ground-tracking are demonstrated in terms of receiver operating characteristic curves.

1. INTRODUCTION

A variety of systems and algorithms employing GPR sensors have been applied to the problem of landmine detection. The NIITEK/Wichmann GPR system reported in this paper employs a time domain pulsed radar sensor [NIITEK]. The system employs a vehicle-mounted linear array of transmitter/receiver antennas. In addition, a global positioning system (GPS) provides Universal Transverse Mercator (UTM) coordinates [Stott, 1977] to identify the earth-based position of the sensor array at any time.

A variety of methods have been applied to the problem of detecting landmines using GPR. For the case of array-based GPR systems fielded on vehicles, it was shown several years ago that feature based methods outperformed energy detectors [Yu et al., 2000; Gader et al., 1998; Gader et al., 2000, Gader et al., 2001]. This is generally because radar signal returns are usually significantly corrupted by noise from the ground, clutter, and even the radar itself and the pattern of the signal return from a mine could be distinctive, even if the energy of the signal return from a mine was relatively low. Methods used to perform pre-processing of the signal to remove these effects include wavelets and Kalman filters [Carevic, 1999a; Carevic, 1999b], subspace methods and matching to polynomials [Gunatilaka et al., 2000], subtracting optimally shifted and scaled reference vectors [Brunzell, 1999], and adaptive extensions of the shift and scale methodology [Wu, 2001].

The most significant among the various interferences in GPR data is the ground bounce, which is the radar reflection from the ground due to the large dielectric discontinuity between air and soil. It is extremely difficult to detect mines without first removing ground bounce. Since ground bounce oftentimes dominates the GPR signal, a combination of maximum-detection and time-gating has proven to be an effective approach to removing ground bounce [Gader, Lee, Wilson 2004a] for smooth roads. The essential assumption for using maximum-detection is that the maximum point of each scan is the ground bounce peak and therefore maximum-detection is equivalent to detection of ground bounce peak. However, if for example vegetation on the ground comes in touch with radar, it gives rise to signal even stronger than the ground bounce. Under such a circumstance, using maximum-detection will fail to locate the ground bounce peaks and make ground bounce removal defective and so more sophisticated methods need to be investigated for off-road or rough road situations.

An apparent remedy for the above predicament is to track the ground, not the maximum value of each scan. To track the ground in the down-track direction, we record all possible candidates for ground bounce peak (peak candidates) of each scan and all paths each of which consists of one peak candidate at each scan. Each of the recorded paths is considered possibly the real ground. Based on the assumption that the vehicle carrying the GPR does not go over ground that fluctuates much, only the one path that exhibits the smallest displacement (fittest survivor) is kept when a decision needs to be made. Keeping the fittest survivor has proved to successfully track ground for terrains of various characteristics. As ground is being tracked, it is

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a straightforward matter to align and time-gate the GPR data to remove ground bounce.

After ground bounce removal, the GPR data is pre-screened by using a CFAR-based algorithm [Gader, Lee, Wilson 2004], and alarm candidates are recorded for further processing. Several radar-energy based features are computed for each of the alarm candidates to detect subsurface anomalies that have mine-like appearance. It is likely that only a small subset of the collected features carry important information. To prune the redundant or un-needed features and weight the remaining features accordingly, a much better way than exhaustive trial-and-error approach is to learn via gradient descent the weights of filters that are applied to the collected features. Specifically, FOWA networks [Gader, et.al. 2004b] are used to classify the alarms reported by the CFAR-based pre-screener.

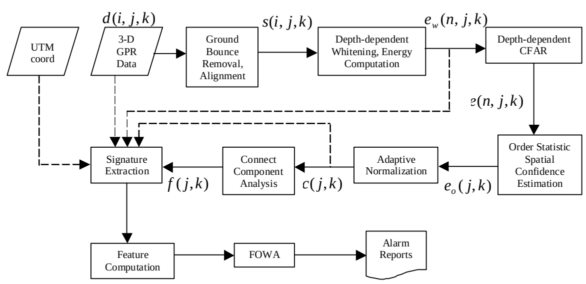

Fig. 1. A block diagram of the FOWA landmine detection algorithm.

2. ALGORITHM DESCRIPTION

A block diagram of the landmine detection algorithm is shown in Fig. 1. The inputs to the process are raw GPR signals sampled by the vehicle-mounted antennas as it travels forward. The Wichmann GPR of NIITEK is used to collect 24 channels of data. Adjacent channels are spaced approximately 5 centimeters apart in the cross-track direction (see Fig. 2). One scan, defined as the measured waveform that is collected at one down-track position, is taken at each approximately 5-centimeter down-track interval. The signal at each cross-track and down-track position contains 416 time samples at which the GPR signal return is recorded. Each sample corresponds to approximately 8 picoseconds. Assuming constant velocity, the depth a radar signal travels is proportional to the time that elapses between when the signal is emitted and when the signal return is recorded by the radar, so time and depth are approximately interchangeable variables for indexing the signal traveling along depth. We often refer to the time index as depth although, since the radar wave is traveling through different media, this index does not represent a uniform sampling of depth. Thus we model an entire collection of input data as a three-dimensional matrix of sample values, $d(i,j,k)$, $i=1,2,\cdots,I$, $j=1,2,\cdots,J$, $k=1,2,\cdots,K$, where the indices i, j, and k represent depth, cross-track position, and down-track position respectively.

In addition, UTM coordinates, $x(j,k)$ and $y(j,k)$, associated with scan position are also inputs to the algorithm. The result of our computation is a collection of alarm reports. Each report contains the UTM coordinates of the positions at which the algorithm declares a mine to be present and a confidence value associated with each position.

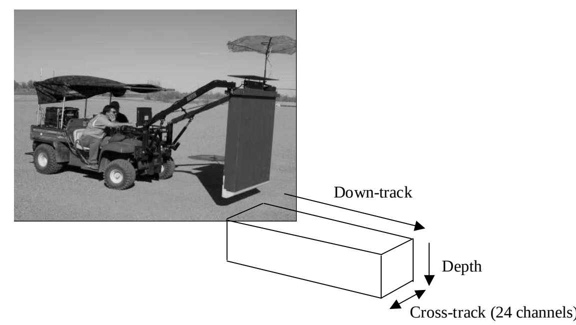

Fig. 2. A picture of the NIITEK/Wichmann GPR. The depth, cross-track, and down-track directions are also identified.

2.1. Ground Bounce Removal and Alignment

In many GPR systems, including the NIITEK/Wichmann GPR, the ground bounce oftentimes dominates the rest of the signal (see Fig. 3). For previous on-road tests, we exploited this property to identify the location of the ground by detecting the maximum value of each scan. After the maximum-detection, alignment is necessary because a vehicle-mounted system cannot maintain the radar antenna at a fixed distance above the ground, so the ground location in the signal may change from scan to scan.

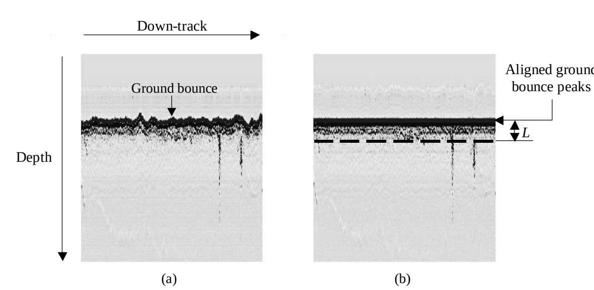

Fig. 3. (a) A vertical slice of raw GPR data; (b) Aligned GPR data with the time-gating line (dashed line) superimposed, where L is the time-gating length.

To align and then remove the ground bounce, we construct our time-series at each location (j,k) using time-gating. The time-series to be processed starts L time samples after the ground bounce peak in the measured time domain signal. Specifically,

For every j and k, Do

$$i^* = \arg\max_i d(i, j, k)$$

$$s(i, j, k) = d(i + i^* + L, j, k)$$

End

L is determined based on the length of the ground bounce in time. The reflection from the ground is measured over several time samples and L is chosen to be 25 time samples so that the contribution from the ground is low. The physical distance corresponding to L varies with soil properties but is about 6 cm in air and can vary from 1.5 to 4 cm in different soils.

The above methodology is based on the assumption that the ground bounce dominates the GPR signal. It works satisfactorily when the assumption is correct. The assumption, however, is incorrect when radar reflections from certain types of metal mines happen to be stronger than the ground bounce or when collecting data over grassy area the radar sensors come in touch with vegetation on the ground and the contact between vegetation and the radar gives rise to signal stronger than the ground bounce. To locate the ground bounce peaks and also account for ground bounce that does not dominates the GPR signal, other approaches must be taken. We propose tracking the ground by determining the "fittest survivor".

To find the fittest survivor, we process each channel of the GPR data independently. Since the ground bounce peak is at least a local maximum of one scan, given the peak or peak candidates $\{P_1^{k_1}, P_2^{k_1}, \cdots, P_{n(k_1)}^{k_1}\}$ at a previous scan (scan k_1), those points that satisfy the following conditions are considered the peak candidates at the current scan (scan k_1+1): (1) the displacement between the point and any peak or peak candidate at the previous scan is not larger than 15 sample points; (2) the point has a value no less than 1/10 of the maximum value at the current scan. The premises for the two conditions are: (1) the ground does not fluctuate much between adjacent scans; (2) the ground bounce peak should not be significantly lower than the maximum value. Suppose the peak candidates at scan k_1+1 are $\{P_1^{k_1+1}, P_2^{k_1+1}, \cdots, P_{n(k_1+1)}^{k_1+1}\}$. Having $\{P_1^{k_1+1}, P_2^{k_1+1}, \cdots, P_{n(k_1+1)}^{k_1+1}\}$, we move on to the next scan and determine the peak candidates $\{P_1^{k_1+2}, P_2^{k_1+2}, \cdots, P_{n(k_1+2)}^{k_1+2}\}$ at scan k_1+2 in a same way. Any path consisting of $P_x^{k_1}$, $P_y^{k_1+1}$, and $P_z^{k_1+2}$, where $x \in \{1,2,\cdots,n(k_1)\}$, $y \in \{1,2,\cdots,n(k_1+1)\}$, and $z \in \{1,2,\cdots,n(k_1+2)\}$ is considered a possible candidate to be the true ground bounce between scan k_1 scan k_1+2. Whenever multiple paths converge to the same point, only the path that exhibits least maximum displacement is kept. In case of a tie, the path that has a smaller sum of displacements survives. The lone path that survives is the fittest survivor out of the group of convergent path. Each group of convergent paths produces one survivor, and all those paths that do not belong in any converging groups are also kept for further processing. In a same fashion, candidate paths either grow or get eliminated after one scan is taken in for processing. To initialize the tracking process, for the first scan any point which is within 50 sample points from the maximum point and is no less than 1/10 of the maximum value is kept as a peak candidate. For real-time application, a decision must be made before accumulating 30 scans (corresponding to 1.5m) so only one path survives, whether paths converge or not. An example is given in Fig. 4, where a vertical slice of un-processed raw GPR data is shown in Fig. 4(a), and above the ground bounce is signal due to vegetation on the ground coming in touch with the radar sensors. Since the signal due to the vegetation is even stronger than the ground bounce, maximum-detection does not correctly track the ground bounce, as is evident in Fig. 4(b). On the other hand, by keeping fittest survivors, we track the ground successfully as in Fig. 4(c).

After tracking ground by means of determining fittest survivors, data is aligned by aligning the ground bounce peaks. The aligned data is then time-gated to keep only the portion of data that is L time samples after the aligned ground bounce peak. Plots of aligned, time-gated data are shown in Fig. 5, where alignment was preceded by detection of maxima in Fig. 5(a) and alignment was preceded by tracking of ground in Fig. 5(b). Since tracking of maxima in Fig. 4(b) erroneously tracked the signal due to vegetation, the alignment that followed was problematic in the sense that portions of ground bounce were shifted downward as can be seen in Fig. 5(a). If a number of consecutive channels suffer from the problematic alignment, the erroneously shifted ground bounce might form a spurious structure that has mine-like features. Spurious alarms then will be recorded. On the other hand, by keeping the fittest survivors to track the ground, alignment was correctly done as can be seen in Fig. 5(b) and no spurious alarms result.

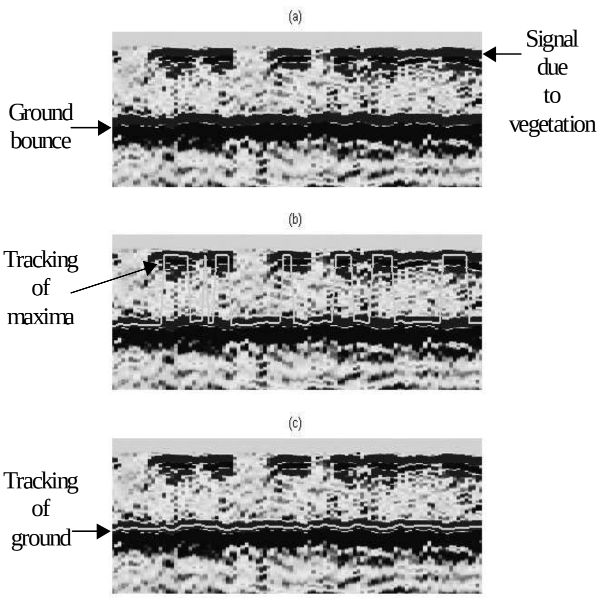

Fig. 4. (a) A vertical slice of raw GPR data where signal due to vegetation is clearly seen; (b) tracking of maxima; (c) tracking of ground.

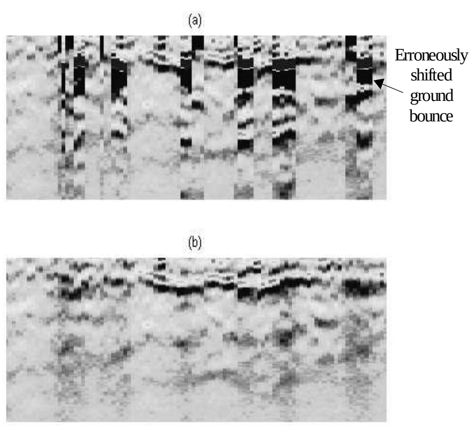

Fig. 5. (a) Aligned, time-gated data after maximum-detection; (b) aligned, time-gated data after ground-tracking.

For detailed discussions about the remaining steps, including depth-dependent whitening, CFAR, order statistic, adaptive normalization, connected component analysis, signature extraction, feature computation, and FOWA, see [Gader, et. al., 2004a, 2004b]. Only a brief summary is given herein. The aligned, time-gated data is whitened and reduced in dimensionality, resulting in depth bins. A CFAR algorithm is applied to each of the depth bins and depth bins are aggregated via order statistic. The components of the adaptively normalized, aggregated CFAR output are analyzed and regions of interest are identified for feature extraction and classification via a network structure that optimizes the use of the features over the depth bins. The end result of all the processing is a report of alarms that records information such as the UTM coordinates of alarm locations and confidence values for alarms.

3. EXPERIMENTAL RESULTS

As has been reported, the Wichmann GPR achieved orders of magnitude reductions in false alarm rate (FAR) over other systems in *blind tests* on simulated roads with buried mines, called lanes. Data collected by NIITEK were provided to algorithm developers who ran fully automated detection software on the data. Detection software produced reports of alarms. IDA scored the alarms and the scores were presented in terms of Probability of Detection (PD) vs false alarm rate. These quantities are computed by thresholding alarms' confidence values to produce Receiver Operating Characteristic (ROC) curve. Once alarm reports were submitted to IDA, the GPR data was erased from the disks of the algorithm developers and NIITEK [Torrione and Collins, 2003, Gader, Lee, and Wilson 2004a].

Those tests were conducted on lanes that had been built to simulate roads. Due to the excellent performance on lanes, it was decided that the further research and development should rely on data collected in more realistic environments. Therefore, GPR data was collected in a variety of locations that were not simulated roads. Some of these locations were off-road areas such as grassy areas whereas some of them were "natural roads" in remote areas of Army bases. Short descriptions for the natural areas over which data was collected are given in Table 1.

Natural Area	Characteristics
RN21	Road with tall grass
FP23	Gravel road
71AHQ gravel	Gravel road
71AHQ grass	Grassy area along side of a gravel road
71AHD	Grassy field
HR	Mixture of gravel, grass, and dirt-ruts beside a road

Table 1. Natural areas over which GPR data was collected.

For each natural area, GPR data was collected over a 1.2 meters wide swath for 500 meters. For logistical reasons, no mines were buried in these areas. Since many of the natural areas did not have mines, to compute Probability of Detection (PD) vs the False Alarm Rate (FAR, in number of false alarms per square meter), an alarm file for a lane at a different location was created. For each threshold, the PD was computed

for the lane and the FAR was computed for the natural area. The detection algorithm was run on each data set with and without ground-tracking. See Fig. 6 for ROC curves for the natural areas listed in Table 1. The improvement rendered by ground-tracking is significant.

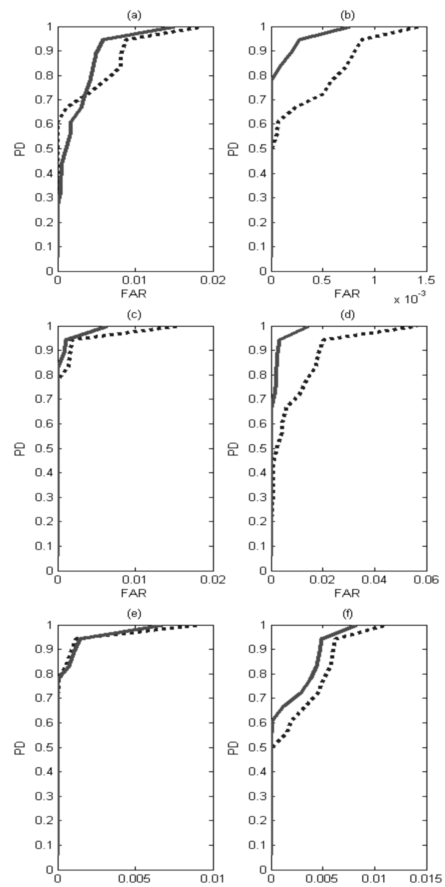

Fig. 6. Comparisons of PD vs FAR between detection with and without ground-tracking. Dotted curves are without ground-tracking, and solid curves are with ground-tracking: (a) RN21, (b) FP23, (c) 71AHQ gravel, (d) 71AHQ grass, (e) 71AHD, and (f) HR. Note that different scales are used in sub-figures.

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CONCLUSION

The NIITEK/Wichmann GPR achieved orders of magnitude reductions in false alarm rate over other systems. To further reduce FAR in situations for which the ground bounce is not the dominant signal, ground tracking was implemented. Experiments show that ground-tracking provides improvement over detection without ground-tracking.